Combining Individual and Firm-level Human Capital Resources: The Creation and Performance Benefits of Human Capital Alignment

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Abstract:
We investigate how alignment between firm and individual-level human capital resources influences firm performance. We argue that a high degree of alignment between the firm and individual levels increases human capital utilization, coordination, and transfer. Drawing on Utah residential real estate data from 1996-2014, we find that brokerages with higher brokerage-agent human capital alignment engage in more transactions than brokerages with lower alignment. These benefits increase with firm size. We also find that individual-level human capital similarity in the first year significantly influences firm-individual alignment in subsequent years. These results suggest that managers from founding onward must carefully craft and manage alignment in individual and firm-level human capital resources to generate persistent performance advantages that are resistant to turnover and difficult for competitors to replicate.

Keywords: Human capital, microfoundations, real estate, utilization, complementarities, aggregation

INTRODUCTION

Organizing individual-level human capital as a firm-level resource lies at the heart of firm strategy and performance in knowledge-intensive industries. Such human capital is often general, broadly applicable across firms, but can be specific to individual firms in its use (Lazear, 2009). Central to creating competitive advantages from human capital are complementarities between individuals (Campbell, Coff, and Kryscynski, 2012a; Ployhart *et al.*, 2014; Raffiee and Byun, 2019) and coordination and transferability of knowledge within the firm (Garicano, 2000; Kogut and Zander, 1992, 1996; Zenger, Felin, and Bigelow, 2011), which allows the firm-level human capital resource as a whole to become something greater than the simple sum of the individual-level parts. Recent work has made great strides in understanding the relationship between human capital and performance at the individual level in knowledge-intensive industries (e.g., Zwick et al. 2017; Byun, Frake and Agarwal, 2018; Gubler and Cooper, 2019; Raffiee and Byun, 2019; Nagle and Teodoridis, 2020). However, significantly less is understood regarding the creation and performance implications of human capital resources at the firm level, and empirical evidence to date remains sparse (Barney and Felin, 2013; Fulmer and Ployhart, 2014; Ployhart *et al.*, 2014). Yet, such an understanding lies at the heart of creating firm-level competitive advantages from heterogeneous individual-level human capital resources.

In this paper we investigate how individual-level human capital resources in a single professional service setting combine with the existing firm-level human capital resource to engender high firm-level performance. We argue that alignment between the firm level and individual level human capital resources allows for greater utilization of both individual and firm-level human-capital resources, increases human capital transfer between individuals and the firm, improves coordination within the firm, and engenders complementarities. Together this improves individual-level productivity, and subsequently firm-level performance. Such benefits increase with firm size – as firm-level human capital resources are more fully utilized with scale – and is particularly beneficial to firms that have specified firm-level human capital strategies. Finally, we argue that the firm-level human capital resource is initially cultivated in nascent firms through similarity of the initial individual-level human capital resources. Such similarity improves human capital transfer from the individual level to the firm level and creates improved opportunities for firm-individual human capital alignment in future periods.

We examine these theoretical arguments in the residential real estate industry. To measure human capital profiles at the individual and firm levels, we construct time-varying agent- and brokerage-level profiles based on the zip codes in which agents and brokerages represent buyers or sellers. These profiles dynamically capture underlying individual or firm knowledge and skills based on area-specific components. We compare current individual-level human capital profiles to the historic human capital profile of the brokerage to arrive at a measure of firm-individual (or brokerage-agent) human capital alignment. When individual-level human capital profiles overlap significantly with the historic record of the brokerage, this indicates high firm-individual human capital alignment. We also compare the human capital profile for each agent to those of other agents employed in the same brokerage to arrive at a measure of individual human capital similarity. When individual-level human capital profiles overlap significantly, we see this as indicative of high agent-agent (individual-level) human capital similarity. We then utilize dynamic data on human capital profiles at the individual and firm levels, and on the degree of individual similarity at entry, to estimate 1) how brokerage-agent human capital alignment is associated with brokerage performance, measured as the number of homes transacted by a brokerage (either on the buy or sell-side) in a year, 2) how the association changes with firm size and with different established firm-level human capital strategies, and 3) how initial individual-level human capital similarity is associated with firm-individual alignment in subsequent years.

Using data on 1,423 real estate brokerages in two populous counties of Utah from 1996-2014, we find that brokerage-agent human capital alignment is positively related to brokerage performance, such that brokerages engage in more real estate transactions when brokerage-agent fit is high. Our results suggest a one-standard deviation increase in alignment associated with an increase in the range of 2.5-12.1% in the number of homes transacted by a brokerage in a given year. These performance-enhancing benefits of brokerage-agent human capital alignment are higher for larger brokerages than smaller brokerages, measured as the number of agents employed by the brokerage. Finally, we find that post-entry alignment is positively associated with the degree of similarity in individual-level human capital at brokerage entry, as brokerages with higher initial agent-level similarity have higher subsequent levels of brokerage-agent human capital alignment in future years.

These results make a few important theoretical contributions. First, they respond to calls to investigate multi-level issues in human capital, including how human capital aggregates to the organization level (Barney and Felin, 2013; Lazear, 2009; Lepak and Snell, 1999; Nyberg *et al.*, 2014; Ployhart *et al.*, 2014; Ployhart and Moliterno, 2011). Our theory and results suggest that individual-level human similarity plays a key role in determining the creation of firm-level human capital resources. Second, these results contribute theoretically to work in human capital and the microfoundations of strategy by showing how micro-macro links in human capital influence firm performance in knowledge-intensive settings (Barney and Felin, 2013; Campbell *et al.*, 2012b; Raffiee and Byun, 2019; Zenger *et al.*, 2011). Human capital utilization at the firm and individual levels, in conjunction with higher coordination, increased complementarities, and improved human capital transfer between the firm and individual levels appear important to unpacking such links. Third, our paper speaks to the recent debate about the importance of general human capital and human capital fit to performance (Campbell *et al.*, 2012a; Lazear, 2009; Crocker and Eckardt, 2014; Ployhart and Cragun, 2017; Weller et al., 2018; Raffiee and Byun, 2019), by showing that value-creating human capital specificity may be determined by the alignment between firm and individual-level human capital resources. Thus, alignment may function as an important isolating mechanisms that restricts employee mobility and leads to further cospecialization of individual-level human capital resources (Coff and Kryscynski, 2011; Campbell, Coff, and Kryscynski, 2012). Finally, these results provide empirical evidence on the important role firm-level human capital resources play in performance, which has proven difficult to estimate empirically.

These results likewise have important implications for business practitioners and managers. First, they suggest that a human-capital based entry plan is important to building a strong firm-level human capital resource. Thus, entrepreneurs should carefully consider how the initial human capital of workers they hire will influence their firms' human capital resource in the future. Second, managers should carefully contemplate the degree of firm-individual human capital alignment when hiring workers after entry. While hiring "superstar" employees may be appealing, such individuals may not necessarily benefit from or contribute to the firm-level human capital resource, which indicates an important tradeoff for managers. Finally, these results suggest that firms can generate successful human-capital based advantages by carefully crafting a firm-level human capital resource. Such a resource is unlikely to be imitated away quickly and can be resilient to employee turnover. Importantly, the value of this resource increases with the size of the firm.

THEORETICAL BACKGROUND

Human Capital is a Multi-Level Resource

Human capital has been defined as the knowledge, skills, talents, abilities, health, and other attributes of individuals that can be drawn on for productive uses (Smith, 1776; Becker, 1964), including by firms to fulfill firm-level objectives (Lazear, 2009; Ployhart and Moliterno, 2011; Ployhart *et al.*, 2014). The firm-level human capital resource is unique when compared to other firm resources because parts of it can be embedded at either the firm or the individual level. Understanding this multilevel nature, and the interplay between the firm and individual levels, is essential to explaining the performance and functioning of the whole (Felin and Foss, 2005; Ployhart *et al.*, 2014). Recently scholars have sought to better characterize the firm-level human capital resource, including the extent to which it can inhere independent of individuals employed at the firm (e.g., Campbell *et al.*, 2012b; Crocker and Eckardt, 2014; Nyberg et al., 2014; Raffiee and Byun, 2019). In this paper we add to this effort by developing and testing theory surrounding multi-level human capital resource alignment. Our focus is on understanding how alignment between the established firm-level human capital resource and the currently employed individual-level human capital resources develops, and how it influences firm performance.

To understand this concept of alignment, we must consider human capital at each level. While human capital at the individual level is relatively straightforward, human capital at the firm level is more difficult to conceptualize, as some pieces of this resource may be a direct result of the individuals that currently work at the firm, and other pieces may inhere independent of the individuals who work there. For instance, a firm cannot typically possess skills independent of its employees. It can store knowledge of how to engage in productive activities, but knowledge and skills are distinct. Skills usually only exist in a firm if individuals in the firm currently possess them.[1] Conversely, knowledge can be codified and embedded in a firm in its training materials and other means of storage. The firm may also have reputation, training programs, or social networks that inhere even with employee turnover, but which can be drawn on by current employees for productive uses.[2] Thus, even if the firm lost all of its employees, the owner could hire new employees and provide resources that would

[1] One potential objection to this statement could be that capabilities can be embedded in machines. But such machines would rightfully be considered physical capital, not human capital.
[2] While human and social capital are distinct concepts and have been shown to each influence performance in real estate (Gubler, 2018; Gubler and Cooper, 2019) we treat social capital as a subset of human capital in this paper.

lower training costs and improve individual productivity in the knowledge and skill spaces to which the firm's human capital resources apply.

While the firm-level human capital resource can thus be separated into two non-mutually exclusive categories, elements of the human capital resource at both levels have the potential to be transmitted across levels, which influences the stock of the human capital resources at each level. For instance, a surgeon may transmit human capital from the individual level to the firm level by developing training materials that can be used to train future surgeons and nurses in a practice to successfully use tools and procedures to perform robotic surgeries. If these materials are used at the practice with success, and reputation accrues to the practice as a result, additional human capital is transmitted to the firm level from that individual surgeon. Transmission from the firm to the individual level is even more intuitive and has been more clearly documented in both literature and practice (e.g., Kogut and Zander, 1992; Chan, Li, and Pierce, 2014; Collins and Kehoe, 2017; Cascio, 2019). For instance, new-hire training from firm-level codified knowledge and resources, such as printed materials, videos, or mentorship programs, increases individual knowledge and skills needed to perform jobs successfully. In either case, human capital that existed at one level becomes embedded in the other.

The above logic surrounding human capital transfer between individuals and the firm raises questions about the boundary conditions of transferability. That is, what limits the transferability of human capital across levels? A simple answer is that any knowledge, skills, or other abilities that can be communicated can be transferred. This implies that tacit human capital, which by definition cannot be communicated, is the subset of human capital whose transferability is in doubt. However, tacit human capital may also be transferred between levels, but perhaps only imperfectly. For instance, tacit human capital that comes through learning-by-doing can be transferred between levels through example and observation (e.g., Chan, Li, and Pierce, 2014), but the efficiency of this transfer depends on observability and the understanding of the observer(s). Individual reputation may similarly accrue to organizations without direct efforts from individuals, and vice versa. Certainly, the firm would like to transfer any productivity-related human capital to its employees that it can. However, the individuals in which human capital is embedded are not owned by the firm (Campbell *et al.*, 2012b; Coff, 1997), and it can be very costly for the firm to transfer human capital to individuals if they then leave the firm to pursue other opportunities. Individuals face similar risks when considering whether to transfer human capital to the firm, as their ability to appropriate value from it decreases the more widely it is held.

Thus, while individual-level human capital has generally been shown to positively correlate with firm outcomes (e.g., Ching, Forti, and Rawley, 2019; Gubler and Cooper, 2019; Raffiee and Byun, 2019; Rosen, 1983; Zwick et al., 2017), less is known about whether, when, and how it works in concert at the firm level to influence firm-level outcomes (Ployhart *et al.*, 2014). Yet, one reason the firm has been theorized to exist is because of its ability to efficiently coordinate and organize individual-level knowledge and skills (Conner and Prahalad, 1996; Garicano, 2000; Kogut and Zander, 1992, 1996; Zenger *et al.*, 2011), which can subsequently lead to the formation of valuable firm-level human capital-based resources that inhere even after any single employee has left the firm. Previous work has likewise argued that complementarities from general human capital at the firm level can potentially lead to sustained competitive advantages and performance outcomes that are more than the sum of the individual parts (Campbell *et al.*, 2012a; Ployhart *et al.*, 2014), yet little is known about how such complementarities are fostered. Consequently, more work is needed to understand how and when this firm-level resource is cultivated and how and when it can influence firm-level performance outcomes.

Primary and Supporting Human Capital

Human capital can additionally be bifurcated based on the extent to which it drives the core firm-level value-creating activities. If individual-level human capital directly contributes to production – i.e., the creation and delivery of value to consumers – we consider this to be *primary* human capital. This would include for instance lawyers in a law firm, agents in a real estate firm, or dentists and hygienists in a dental office. If the human capital acts to support individuals with primary human capital and does not directly contribute to the creation and delivery of value to consumers, but instead supports those that do, we consider this as *supporting* human capital. While both types of human capital are essential to value creation in firms, we expect primary human capital to exert a larger positive or negative force on the performance of the firm, particularly at the founding stages. Moreover, supporting human capital is typically brought into the firm or cultivated after primary human capital pieces are in place, usually to allow for greater productivity of individuals in the firm with primary human capital. In this paper we primarily focus on primary human capital, although our theory does also explain aspects of how supporting human capital is created and how it might influence primary human capital and firm performance.

Performance Benefits of Aligning Firm-level Human Capital with Individual-level Resources

We argue that the benefits a firm receives from its human capital resources depend in part on the degree of alignment between the firm's current individual-level primary human capital resources and the existing firm-level human capital resource, which has accrued to the firm from the past activity of individual human capital resources. If the current individual-level human capital resources align well with this historical firm-level profile, and if the knowledge and skills from the historical profile continue to be in demand from consumers,[3] then the firm will benefit in performance.

In cases of high alignment, individual-level human capital will be highly utilized at the firm level, and complementarities will exist between the productive activities of employed professionals. Human capital transfer between the individual and firm levels will also be more efficient in terms of

[3] We will confine our treatment of the topic to the static world and will discuss dynamic implications in the limitations section.

time for and amount of accumulation, as familiarity with the relevant knowledge and skill domains will make communication and observation more effective. The firm-level human capital resource will also be highly utilized, which may boost individual-level knowledge, skills, and abilities. This leads to increased performance for the current set of employees in the firm, which ultimately improves firm performance.

Conversely, if there is a low degree of alignment between the currently employed individual-level human capital resource profiles and the historic firm-level human capital resource, then currently employed individuals will largely function in isolation and will only benefit from the general human capital components of the existing firm-level human capital resource. For instance, divorce attorneys in a law firm that has historically focused on issues related to patent law may still benefit generally from staff support, the general reputation of the firm, and from general firm-level resources that aid in practicing law. However, they will not benefit from the more specific firm-level resources developed in patent law that would otherwise increase their productivity, such as specific trainings, mentorship from other lawyers, or network connections. The absence of familiarity with the relevant knowledge and skill domains in such cases make communication and observation less effective and thus make inter-level human capital transfer less efficient. These issues lead to inferior productivity and performance compared to the first case, as individual-level human capital utilization is lower, the firm-level human capital resource is underutilized, human capital transfer is limited, and complementarities are weak. Thus, we expect higher performance from the firm-level human capital resource when there is a high degree of alignment between the historically created firm-level human capital resource and the currently employed individual-level human capital resource profiles. This leads to our first hypothesis:

Hypothesis 1: Firms with higher firm-individual human capital alignment will outperform firms with lower firm-individual human capital alignment.

While we expect the above relationship to hold on average, we expect the benefits of highly utilized and transferred human capital resources to increase with firm size, conceptualized as the number of individuals currently working in the firm. If individual-level human capital resources are not utilized to their full potential in the firm, this creates a kind of slack that reduces firm performance. However, if the firm-level human capital resource is not fully utilized in a large firm, then the potential complementarities and benefits lost are much larger than for a small firm, as the firm-level human capital resource is typically scalable to some extent. For instance, firm reputation can scale to all professionals without decreasing its productive use. When the individual-level human capital resources align with the firm-level human capital resource, this consequently provides opportunities for benefits to all professionals employed at the firm. This results in more productive professionals, and the benefits increase with firm size if the resources are scalable.

Even in the case where firm-level resources cannot scale entirely with size, the benefits are still larger compared to small firms as the firm-level human capital resource is more fully utilized. For instance, while support staff may not be able to provide assistance to all professionals in the firm, having scale allows the firm to fully utilize supporting human capital resources. Consequently, when the level of alignment is high between the firm-level human capital resource and the currently employed individual-level human capital resources, scale should lead to larger performance gains compared to when firm size is small.

Finally, larger firms may be better able and more motivated to support transferability of human capital between the individual and firm levels. If larger firms can benefit in productivity from the scalability and high utilization of the firm-level human capital resource, then larger firms should be more willing to devote resources to its transfer than small firms. Large firms consequently should be more likely to support training and mentorship programs and the development of materials that codify knowledge to increase the efficiency of transfer. They similarly should be more willing to invest in supporting human capital resources, such as training and administrative staff, which support the transfer of human capital between levels. Conversely, small firms may not be able or willing to bear the cost of these resources, given the more limited benefits of human capital transfer from their limited scale. Our second hypothesis follows:

Hypothesis 2: High firm-individual human capital alignment is associated with larger performance gains for large firms compared to small firms

In addition to firm size, we also expect firm-individual human capital alignment to be beneficial for firms that have a well-established firm-level human capital strategy. These strategies might be focused on specialization in a knowledge or skill area, specialization in a certain area of the market such as those areas with high demand, or around firm growth and increased market reach. Such strategies dictate how and to what extent a firm should grow, who they should hire, how and where they should compete, and the relationship between the individual and firm-level human capital resources. A firm with a well-defined human capital strategy must build a firm-level human capital resource to support that strategy and to glean its accompanying performance benefits. This in turn requires individual workers whose human capital is tailored to take advantage of the strategy's unique features and the developed firm-level human capital resource. Thus, alignment between the firm and individual-level human capital components allows the firm to be productive in its chosen human capital strategy and to deliver value to clients. Specializing in a firm-level human capital strategy is by its nature limiting to the firm, as the firm engages in tradeoffs. To augur benefits from these tradeoffs the firm consequently needs to bring in individuals whose individual-level human capital aligns with the firm's specified human capital strategy (and the accompanying firm-level human capital resource) to foster complementarities and increase human capital transfer that will in turn create value within that strategy. This leads to our third hypothesis:

Hypothesis 3: High firm-individual human capital alignment is associated with larger performance gains for firms with a specified firm-level human capital strategy compared to firms without a specified firm-level human capital strategy.

Creating Alignment between Firm and Individual-level Human Capital Resources

Finally, given the potential importance of human capital alignment to firm-level outcomes, the question naturally arises as to how alignment can be fostered. For an established firm this is relatively straightforward: established firms should simply hire individuals whose knowledge and skills align with the firm-level human capital resource already in existence in the firm. However, for nascent firms, the process of creating future opportunities for alignment is less straightforward and has yet to be unpacked in the literature.

We argue that while firm-level human capital resources can be built by firms over time, decisions at entry play an outsized role in this process. At entry, the firm-level human capital resource is largely non-existent, such that an entrant firm is most often just a sum of the individual-level human capital components embedded in employees. However, the initial nature of these individual-level resources, in relation to each other, may lead to path dependencies in the establishment of the firm-level human capital resource. When an entering firm has similarity in individual-level human capital resources, meaning that the knowledge and skills of the individual employees have a high degree of similarity with each other, this increases human capital transfer from the individual to the firm level. This increased rate and magnitude of human capital transfer between levels aids in the creation of the firm-level human capital resource and creates increased opportunity for future firm-individual human capital alignment. Thus, the initial individual-level human capital resources may set a firm on a sticky or path dependent path, which then influences future alignment and the firm's human capital strategy. Our final hypothesis follows:

Hypothesis 4: Firms with high individual-level human capital similarity in the first year will have higher levels of firm-individual human capital alignment in the future compared to firms with low initial individual-level human capital alignment.

EMPIRICAL SETTING: RESIDENTIAL REAL ESTATE

The ideal experiment to test our hypotheses would involve constructing human capital profiles for individuals and firms over time. These profiles would dynamically capture the key elements of an individual's knowledge and skills, and the nature of the firm-level human capital resource across time. We would then randomly assign individuals (and their human capital profiles) to firms, including at founding, and examine the emergence and performance of the firm-level human capital resource. That is, we would investigate how the human capital resource causally drives firm-level performance, based on different individual-level human capital resource profiles assigned to the firm and the nature of the firm-level human capital resource that emerges.

While this ideal is unrealistic, the residential real estate industry in Utah is a promising setting for examining these questions. Because our data are employer-employee matched, we can follow individual human-capital resources throughout time between firms. We likewise can observe historic and current members of the brokerage and their accompanying human capital profiles. Thus, the knowledge and skills underlying this industry are more observable than in many other settings, and data at both the individual and firm level are well documented and detailed. Performance is also cleanly measurable and strongly driven by human capital. Finally, this setting is promising because the residential real estate industry in the United States is large and important to understand for scholars and practitioners alike, with 5.34 million existing homes sold in 2019 at an average price of $308,600.[4] Moreover, while we are not claiming causal identification in any of our analyses, the knowledge-based

[4] https://cdn.nar.realtor/sites/default/files/documents/ehs-11-2020-overview-2020-12-22.pdf

nature of this professional service industry provides confidence that the associations we are finding likely present themselves in many settings.

Real estate brokerages (also referred to as offices) are the individual firms in our setting. Real estate agents legally must work under a licensed brokerage, and under a real estate broker, in order to work with buyers and sellers in transactions. Brokerages may be sole proprietorships, independent, or franchised. Real estate brokerages employ agents to help clients buy and sell homes. Listing agents primarily assist in preparing the home for sale, pricing the home, marketing the home, negotiating with opposing agents, and completing the necessary legal documents needed to transfer ownership between parties. Buying agents primarily assist buyers in finding homes, placing offers, negotiating with sellers and opposing agents, and completing the documents necessary for sale.

Real estate agents, and consequently their employing brokerages, often focus in geographic areas. This focus allows them to develop the knowledge and skills necessary to succeed in that area. Such knowledge and skills may readily apply to that area but only distantly to other areas. For instance, agents may have important knowledge about neighborhoods that allows them to effectively market a home, or to find an appropriate buyer. They may also have strong social networks and contacts that improve the client experience.

The geographical aspect of residential real estate allows us to generate individual-level human capital profiles based where an agent has previously sold homes. We do this using area zip codes. Agent human capital profiles then are conceptualized by the profile of zip codes they have historically sold in, and the number of homes in each area. At the firm level, the firm's human capital resource then entails the historical profile of the firm, based on the buying and selling activity of agents that previously worked for the firm. These profiles allow us to capture where an individual or firm has worked previously and the likely knowledge and skills that are consequently developed.

This setting likewise allows us to observe the founding of real estate brokerages and the entry of individual agents into the industry across time. When a real estate brokerage is founded it has little (if any) human capital embedded at the brokerage level, because it has no historical behavior from which individual-level human capital can be embedded into the firm level. Most of a nascent brokerage's knowledge and skills are embedded in its agents. Agent human capital is then transferred to the brokerage over time as its agents build firm-level reputation and resources.

DATA AND EMPIRICAL APPROACH

Our dataset is constructed using data from a primary Utah Multiple Listing Service (MLS). The MLS compiles and maintains a database of all properties listed in Utah, making it a primary source of real estate housing information for the region. Our study uses data from Utah and Salt Lake Counties, the most populous counties in Utah, for 1996-2013. This includes more than a half-million home listings by over 17,000 agents (owner listings not included) working for over 2,500 brokerages. The data also include 60 zip codes within which agents actively transact, allowing us to construct experience-based human capital profiles for each agent and brokerage in our sample. We pair these data with data from the Utah Division of Real Estate, which maintains licensing information on brokerages and agents. These data allow us to incorporate agent and brokerage licensing information throughout time.

To construct the final sample used in our analyses, we followed convention from previous real estate papers (e.g., Gubler, 2019; Gubler and Cooper, 2019; Levitt and Syverson, 2008) by excluding listings that appeared to contain errors, such as those reporting zero bathrooms, bedrooms, or kitchens. We also excluded listings with list prices in the top or bottom 1% of the list price distribution. This included dropping listings with list prices below $55,000, as well as luxury homes, which represent unusual windfalls for agents and firms.

Although our dataset begins in 1996, we begin our analyses using data from 2000 in order to provide a "burn-in" period for our specialization and overlap measures. We classified all agents and offices who listed homes in 1996 as left-censored and omitted all left-censored brokerages so that we only included brokerages whose entire histories were in our dataset. We did not omit left-censored agents, as doing so would have limited our ability to analyze their brokerages, but our burn-in period allows us to create reasonable measures of agent characteristics, as our agent characteristic measures stabilize fairly quickly. Our analyses are performed at the office-year level. Because individual-level alignment is measured with respect to other agents in the office, we excluded observations where the office in question had fewer than two agents.

Constructing Individual and Firm-Level Human Capital Measures

Examining our theoretical predictions requires measuring human capital at the individual and firm levels. A useful approach to doing so is to measure training or experience in the different knowledge or skill areas an individual or firm could potentially find valuable (Gathmann and Schönberg, 2010). In our setting, we use experience in each zip code as the basis for our analysis. To construct experience profiles, we examine the set of zip codes in which each agent has listed and the proportion of the focal agent's listings in each zip code. For each agent in a given office, a vector consisting of one entry for each zip code in the dataset is constructed with each component of the vector reflecting the share of the agent's listings in that zip code. With 60 zip codes in the dataset, each agent is consequently assigned a 60x1 vector reflecting the zip codes in which they list homes for a given brokerage and the share of their listings in those zip codes. To correct for differences in demand across zip codes, and the natural advantages that accrue to focusing on certain areas where there may be more listings or listings may be closer together geographically, we then subtract the overall demand share for each zip code since the focal agent's entry from the agent's listing share (Audretsch and Feldman, 1996; Ellison and Glaeser, 1999; Rosenthal and Strange, 2004). We also construct an agent-specific 60x1 vector that measures the distribution of the brokerage's listings in each zip code not including the listings of the focal agent and perform the same demand correction noted above.

Dependent and Independent Variables

Brokerage number of homes transacted yearly. Our primary performance measure is yearly brokerage performance, measured as the number of homes bought or sold by a brokerage in a given year. Our main dependent variable is the natural log of this measure. Brokerage performance is directly influenced by the number of homes transacted in a brokerage, and real estate brokerages seek to buy and sell as many homes as possible in a given year.

Brokerage-agent alignment. The key independent variable for our analyses is a measure of firm-individual human capital alignment. This is measured as the average alignment between the human capital of currently employed agents in a brokerage and that brokerage's established firm-level human capital profile. More specifically, we measure brokerage-agent alignment by calculating the cosine similarity between the agent's experience share vector and the brokerage's agent-omitted share vector. Because we subtract overall demand share from each vector, this cosine similarity measure is bounded between -1 and 1, with higher values representing more similar vectors. A value close to 1 indicates that the focal agent's experience profile is highly aligned with the brokerage's experience profile (excluding that agent). A value close to or below 0 indicates that the focal agent's experience profile has little alignment with the brokerage (excluding that agent). This alignment measure is then aggregated to the office level by taking the average alignment of all agents in the office.

Agent pairwise similarity. In Hypothesis 4, we theorize that opportunity for brokerage-agent alignment is created in nascent firms when individual-level human capital profiles have high initial similarity. We measure individual-level similarity among agents in a brokerage using the same agent-focused experience vectors described above. Similarity between two agents is measured using the cosine similarity of their experience vectors. This measure is then aggregated to the brokerage level by taking the average across all pairs of agents for a given year, leading to an overall agent pairwise similarity measure.

Human capital breadth and depth. In order to properly measure how brokerage-agent alignment is associated with performance, we need to control for characteristics of the firm's human capital profile. First, we measure breadth with the average of the number of zip codes in which the brokerage has worked per year in its history. Second, we measure human capital depth (at the brokerage or agent level) by calculating a Herfindahl-Hirschman Index (HHI) from the vector of zip code shares (before the demand correction). This gives us a measure of the dispersion of the brokerage or agent's past activity. We then multiply this value by the natural log of the number of homes the brokerage or agent has worked on. Depth of human capital requires experience, and a broad experience set can still achieve a measure of depth through enough experience. Third, we also account for brokerage-level human capital depth by counting the average number of agents who have worked in the brokerage per year in its history. The number of agents in a brokerage is calculated by counting every agent who worked on a home as a buyer or seller agent for the brokerage for a given year. Finally, to account for differences in brokerage markets, we control for the average number of listings per year in the zip codes the brokerage has worked in during its history.

Thus, we control for the brokerage-level human capital profile characteristics as determined by history in order to examine how average agent alignment with a profile of those characteristics is associated with brokerage performance. Importantly, our human capital profile measures are updated with each listing. For yearly measures, we use the first value associated with a listing in a given year for each agent or brokerage. Thus, we ultimately examine the relationship between a given firm-level human capital profile that has been developed in the past and the performance of the brokerage for a given year.

Specialized human capital profile characterization. Finally, for our examination of Hypothesis 3, we need to identify specialized human capital profiles from our data. To discover relevant profiles from our data, we used principal components analysis (PCA) (Galbraith and Schendel, 1983;

Campbell-Hunt, 2000; Chen et al, 2020). PCA allows us to understand how the main features of brokerage human capital profiles in our data are co-determined. Doing so requires us to overcome two significant challenges: brokerage size, scope, average demand, and depth are of different orders of magnitude and are heavily determined by factors at entry. For example, in 1999, the average new brokerage had 1.8 agents working in 3.4 zip codes, with an average of 674.6 listed homes in each zip code. In 2004, those numbers had grown to 2.5 agents, 5.3 zip codes, and 1,016.1 listed homes. Thus, observations of these raw numbers at a given point in time without taking into account cohort effects would result in misidentification of profiles. To overcome these issues, we calculated a cohort-specific z-score for each brokerage over its post-entry lifespan in each of the four human capital-profile categories we recognized as important. We then performed PCA on these z-scores to identify how these four factors are related to each other in determining human capital profiles.

The PCA results (found in Table A1 of the Appendix) indicate that there are three principal types of human capital profiles in our data. The first is a profile built on large brokerage size and wide brokerage scope, with low emphasis on average zip code demand and human capital depth. The second is a profile that emphasizes human capital depth without much regard to the other attributes. The third is a profile with an emphasis on high-demand zip codes without much regard to the other attributes. To identify the brokerages that fit into each category, we put all brokerages with size and scope z-scores above one and with demand and depth z-scores below zero into the first group (6.39% of brokerages). Brokerages not in the first group with depth z-scores above one were then put into the second group (16.21%). Finally, brokerages not in either of the first two groups with demand z-scores above one were put into a third group (6.51%). All other brokerages were left un-categorized (70.89%). For robustness, we also included analyses with profiles categorized using z-score cutoffs of zero instead of one, which produced a breakdown of 14.2% in the first group, 40.83% in the second group, 25.92% in the third group, and 19.05% uncategorized. All results shown with these variables are consistent using either categorization method, and the robustness results can be found in Table A2 of the Appendix.

EMPIRICAL MODEL

To investigate the impact of firm-individual human capital alignment on firm performance, we use the following model as our primary specification:

$$Y_t = \alpha + \beta_1 X_t + \beta_2 \text{Brokerage-agent alignment}_t + \eta_t + \varepsilon_t$$

where Y_t is the dependent variable, the log of the number of homes transacted on the buy or sell side in year t, X_t are our controls, η_t are time fixed effects, and ε_t is the error term. *Brokerage-agent alignment$_t$* is our main independent variable of interest, the average alignment between the brokerage and its agents in year t. In addition to the human capital controls described above, we also control for the current-year brokerage size, brokerage geographic scope (number of zip codes), average agent experience, market size (average number of listings in the zip codes where the brokerage works), brokerage age, and time effects through year dummies. These are all associated with current-year performance. We cluster our standard errors at the office level. Summary statistics and correlations for these specifications can be found in Table 1. Of particular note is that most of these variables have heavily skewed distributions; we will correct for this by using their natural logarithms as our dependent variable and controls.

--------INSERT TABLE 1 HERE--------

To investigate the impact of entry-year individual-level human capital profiles on the subsequent firm-individual human capital alignment, we use the following model as our primary specification:

$$H_t = \gamma + \delta_1 X_t + \delta_2 \text{Agent pairwise similarity}_0 + \tau_t + \nu_t$$

Where H_t is our dependent variable, brokerage-agent human capital alignment in year t, where t is a non-entry year. X_t are brokerage controls in year t. Our main independent variable of interest is average pairwise agent similarity at entry, which is subscripted by a 0 rather than a *t* to show that it is fixed across time. We use the same controls in this specification that we used in the previous specification, but also include average agent human capital depth at entry. Standard errors are clustered at the office level. Summary statistics and correlations for these specifications are shown in Table 2.

--------INSERT TABLE 2 HERE--------

RESULTS

Brokerage-agent Alignment and Brokerage Performance

Our examination of hypothesis 1 requires estimating the association between brokerage-agent alignment and brokerage performance. Table 3 contains OLS results with the natural log of yearly brokerage transactions regressed on average brokerage-agent alignment. Models with and without controls are included in the first two columns of Table 3. These results indicate that average brokerage-agent alignment is positively associated with brokerage performance; our uncontrolled estimate shows a one standard-deviation increase in alignment is associated with about a 12.1% increase in the number of homes transacted by a brokerage in a given year (p-value=0.000), while our controlled estimate puts this association at 2.5% per standard deviation (p-value=0.042). These results are consistent with our first hypothesis.

--------INSERT TABLE 3 HERE--------

Brokerage-agent Alignment Benefits Increase with Firm Size

Table 3 columns 3 and 4 contain results interacting brokerage size with brokerage-agent alignment. The uncontrolled coefficients on alignment (p-value=0.096) and the interaction of brokerage-agent alignment with the log of brokerage size (p-value=0.000) indicate that brokerage-agent alignment is more strongly positively associated with performance for larger brokerages, consistent with hypothesis 2. The uncontrolled results indicate that at our median brokerage size of four agents, a one-standard deviation increase in alignment is associated with 24.4% more homes per year (about 6.57 homes more at the mean of 26.96 homes per year), and a brokerage with seven agents (the 75th percentile of our distribution) can expect 32.1% more homes per year (about 15.54 homes more at the mean of 48.36 homes) than a similarly sized brokerage whose alignment is one standard deviation lower. The estimates of the fully controlled coefficients on alignment and the size-alignment interaction do have different signs (both p-values 0.000), but the negative coefficient on the base term is negated by the interaction term for all brokerages with three or more agents. On average, these controlled results estimate the relationship between alignment and performance at 5.1% more homes per year at the median (about 1.38 homes more at the mean of 26.96 homes per year), and 9.6% more homes per year at the 75th percentile (about 4.79 homes more at the mean of 48.36 homes). Figure 1 plots the predicted natural log of homes against alignment based on our fully controlled model, showing the stronger relationship between alignment and performance for brokerages above the size median than for those at or below the median.

--------INSERT FIGURE 1 HERE--------

Brokerage Human Capital Strategy Results

Table 4 contains results for our empirical look at hypothesis 3, that brokerage-agent alignment should benefit firms more when they have a specified firm-level human capital strategy. Our PCA analysis earlier identified three human capital strategies: large brokerage size and breadth, high human capital depth, and brokerage market focus on demand. We consider the latter two to be specialized human capital strategies, as they are associated with reduced brokerage scope, and the first to be a more general strategy. We include a dummy variable for each profile one at a time in the first three columns of Table 4, and then include all dummies in the fourth column. The column 4 results should be the most clear and robust way to approach this analysis, because the relationship between alignment and performance for non-included profiles is lumped into the base alignment coefficient for the first three models. Contrary to our theoretical predictions, we find no clear relationship between brokerage-agent alignment and firm performance for high-demand or high-depth brokerages. The Wald statistic testing whether the sum of the base alignment term and the respective interaction is different from zero has a p-value of 0.11 for the high-depth profile and 0.63 for the high-demand profile. Interestingly, these results may imply that specialized human capital strategies substitute for brokerage-agent human capital alignment, inconsistent with our third hypothesis. In our setting at least, the greatest benefits for alignment appear to accrue to firms that utilize more general human capital strategies, as shown by the positive and significant results for size/breadth focused brokerages. Overall, these results are only partially consistent with hypothesis 3, but suggest an interesting avenue for future work.

--------INSERT TABLE 4 HERE--------

Entry-year Agent Human Capital and Post-entry Brokerage-level Human Capital

Finally, our examination of hypothesis 4 involves estimating how average agent similarity during a brokerage's entry year is associated with average brokerage-agent alignment in subsequent years. These results are found in Table 5. Overall, these results suggest that entry-year agent alignment is strongly positively associated with average brokerage-agent alignment in subsequent years. Columns 1-2 contain results with no controls included (other than depth in column two), while columns 3-4 contain results with our full set of controls. Using our uncontrolled coefficient estimate from column 1, our findings imply that a one-standard deviation increase in average agent similarity during the entry year is associated with about a 0.33-standard deviation increase in average brokerage-agent alignment in subsequent years (p-value=0.000). Using our fully controlled coefficient estimate from column 4, this association is about a 0.18-standard deviation increase in alignment per standard-deviation increase in first-year agent similarity (p-value=0.000). Figure 2 illustrates this relationship more clearly and shows that average agent human capital depth at entry does not impact this result in a practically significant way. Based on the calculation above, this translates to a one standard deviation increase in average agent alignment being associated with a 0.5% to 3.9% increase in the number of homes transacted yearly. This result is consistent with hypothesis 4.

--------INSERT TABLE 5 AND FIGURE 2 HERE--------

Robustness and Extensions

For additional confidence in our main results, and to provide additional insight into our theoretical predictions, we also ran a number of robustness checks and extensions. First, we reran our main models with brokerage fixed effects to take advantage of the panel nature of the dataset. These models estimate how changes in brokerage-agent alignment influence within-brokerage performance. The results are provided in Table A2 (Appendix). It is important to note that while potentially informative, these models may lead to different conclusions for two reasons. First, there is less variation in brokerage-agent alignment within brokerages, as these measures usually stabilize over time and variation overweighs early years of the brokerage's history compared to later years. Analysis of variance of brokerage-agent alignment by brokerage and year indicates that brokerage alone explains over 70% of the variation in alignment. This lack of within-variation in alignment makes our fixed effects specifications somewhat uninformative about the relationship between alignment and performance. Second, these models do not allow for selection effects, where adoption of human capital alignment is endogenous. Instead, these models imply that all firms have similar incentives to improve performance by increasing brokerage-agent alignment.

The brokerage fixed effect results in Table A2 show similar results for our main effect in the fully controlled model. However, the models interacted with brokerage size highlight an interesting result, when contrasted with our main results (which show a positive relationship between brokerage-agent alignment and performance). The column 6 results indicate that for brokerages with only two or three agents, the within relationship between alignment and performance is weak and may be slightly U-shaped. However, starting at the sample median size of four agents, this relationship takes on an inverse-U shape, and the strength of this inverse-U shape increases as brokerage size increases above the median.

Figure 3 depicts this inverse-U relationship more clearly. Separate graphs are included in Figure 3 for brokerages with four or fewer agents (median) and for brokerages with five or more agents. The smaller brokerages show a mostly positive association between brokerage performance and brokerage-agent alignment, with a very slight inverse-U, while the inverse-U is clearly stronger for larger brokerages. Thus, while the benefits of brokerage-agent alignment appear to increase significantly with brokerage size, consistent with hypothesis 2, it also appears that larger brokerages reach a point as alignment increases where additional alignment becomes detrimental rather than helpful to the firm.

--------INSERT FIGURE 3 HERE--------

This inverse-U relationship, and its increase in intensity with brokerage size, has an interesting possible explanation. As agents in a brokerage attempt to align their human capital with that of the brokerage, large brokerages benefit up to a point. However, as agents become more and more similar to each other, and there are many agents, this may lead to costly redundancies and intrafirm competition, which seem to be associated with lower brokerage performance. The results consequently imply that it is possible for firms to have too much firm-individual alignment. These issues of redundancy and intrafirm competition merit further investigation.

Second, we relaxed our PCA classifications to increase the number of firms classified as having specified human capital strategies. This reclassification dramatically increased the classification of firms, as noted earlier in the paper, but potentially at the expense of including firms in each category that in actuality did not have a defined human capital strategy. Our main results, using these relaxed classification measures, are found in Table A3 (Appendix). The results are highly similar to the main results presented in the paper.

Finally, we investigated the relationship between brokerage-agent human capital alignment and agent mobility patterns. Our theory implies that mobility patterns should differ based on firm-individual human capital alignment, as agents with a higher level of alignment should derive benefits from the alignment, and consequently be less likely to move. These results, presented in Table A4, suggest that brokerage-agent alignment is associated with reduced agent turnover and that brokerages with higher alignment do better after agent departures than brokerages with lower alignment. However, these results also indicate that some employee churn appears important to firm performance when there are higher levels of brokerage-agent human capital alignment. This could be because such churn increases the degree of alignment between the individual human capital resources and the firm-level human capital resource by breaking path dependencies established early in the brokerage's history. Unpacking this further could be a fruitful avenue for future research.

Remaining Limitations and Opportunities for Future Research

While we have drawn on novel human capital measures, rich longitudinal data, and accounted for many potential alternative explanations, limitations remain. First, our results are unable to pin down causality in the relationship between firm-individual human capital alignment and performance. While the associations in this paper provide evidence suggesting that firm-individual human capital alignment improves performance, there could be unobserved selection driving this relationship. However, we see this selection as a feature of the paper, and not just a limitation. Understanding why some firms are unable or choose not to align around a strong firm-level human capital resource provides a fascinating avenue for future work.

Second, while the geographic nature of our data has allowed us to robustly measure human capital at both the individual and firm levels over time in a new and novel way, such measures almost always generate tradeoffs. We follow common practice in the labor economics and human capital fields by measuring human capital through experience in specific fields or areas, but we ultimately are not able to measure the underlying knowledge, skills, and abilities of individuals, or to aggregate this up in a clear way to the firm level. While our measure provides a strong improvement compared to previous work that aids in this effort, and likely proxies for these underlying human capital components, it still could be improved upon in future work.

Finally, our results pertain only to a single setting and have a relatively small sample size. While we believe real estate is an important setting to investigate in its own right given its size, and while we believe our theory and results likely generalize to other settings, more work is needed. This includes drilling down into how the nature of human capital at the individual and firm levels might differ between contexts, and consequently alter the relationships we propose. Given the importance of understanding this process and its performance implications in knowledge-intensive industries, we see this as a fruitful avenue for future research.

While we have focused our theory in this paper on a static setting, there are important implications of our theory for dynamic settings that will be important to address in the future to understand the concept of alignment more fully. In a static world, firm-level human capital profiles are built to fit the preferences and resources of the firm's current and potential clientele, and we argue that achieving alignment between individual-level and firm-level human capital resources is important in the effort to create and capture value in the marketplace. However, shocks to the environment can result in rapid and significant changes in preferences, demand, or resources, which could then create a mismatch between the firm-level resource and its competitive context. Understanding how alignment influences the firm's ability to adjust to match a changing landscape and how the firm manages misalignment induced by market changes is important for scholars and managers alike. Such questions warrant investigation in future work.

DISCUSSION AND CONCLUSION

Human capital lies at the heart of performance for knowledge-intensive firms. However, the theory and evidence on how human capital resources at the firm level can be created and managed to improve performance remains thin. In this paper we have developed theory and shown evidence regarding how firm-level human capital resources can be created and leveraged in a single professional service setting to improve performance. Drawing on unique data from residential real estate and using novel dynamic measures of human capital at the individual and firm levels, we have shown evidence suggesting that alignment between the firm and individual-level human capital resources is associated with higher firm performance. We argued that this stems from increased utilization of the individual and firm-level human capital resources, as well as from increased human capital transfer, coordination, and complementarities. These benefits were found to increase with firm size, as this increases the utilization of the firm-level human capital resource. This implies an increased importance of managing human capital resources as the firm grows. Contrary to our prediction, we found that alignment was not clearly associated with better performance in firms with specialized firm-level human capital profiles. Finally, we found that firm-level human capital resources can be cultivated at founding based on similarity across the individual-level human capital profiles. Similar profiles lead to the creation of a strong human capital resource around which firms can organize in the future.

Together the results of this paper suggest that multi-level investigations of human capital resources, as called for recently by scholars (e.g., Felin and Foss 2005; Ployhart and Moliterno, 2011, Ployhart et al., 2014), are critical to understanding firm performance and competitive advantage in knowledge-intensive industries. Such investigations move beyond the classic general vs firm-specific human capital debate in the strategy literature (e.g., Campbell *et al.*, 2012a; Lazear, 2009; Nyberg et al., 2018) or the focus on human resource management systems and employee attraction, motivation, and retention in the human resources literature. The essence of such an approach relies on understanding the fundamental building blocks of firm-level human capital-based advantages, and how human capital functions across levels to influence both individual productivity and firm-level outcomes (Felin and Foss 2005, Ployhart et al., 2014).

To aid in this effort, this paper has sought to combine related literatures and to build on related theories. This includes nascent but growing work on performance and employee-organizational fit (e.g., Crocker and Eckardt, 2014; Ployhart and Cragun, 2017; Weller et al., 2018; Raffiee and Byun, 2020). Our paper has shown theoretically and empirically how alignment can be fostered, and how firm and individual human capital combine to influence performance. Second, we contribute to and draw on organization-level theories, which have focused on coordination and transfer of knowledge and skills to improve firm performance (Chan et al., 2014; Conner and Prahalad, 1996; Garicano, 2000; Kogut and Zander, 1992, 1996; Zenger *et al.*, 2011). Our paper suggests that to have success in coordination, transfer, and in fully utilizing firm-level human capital resources, firms need to carefully consider the nature of the individual-level human capital resources embedded in employees. Finally, we have sought to better understanding dynamics underlying the human capital aggregation process (Barney and Felin, 2013), particularly from human capital resources brought together by firms at entry. Our results suggest firm-level human capital resources can be sticky and path dependent because of human capital entry decisions, which influences future alignment and consequently performance. As scholars continue to focus and build on the above ideas and literatures, we believe the human-capital literature will take a theoretical leap forward. In this regard, we echo calls from recent scholars to engage in new debates about human capital resources and performance (Nyberg et al., 2018).

Finally, the results of this paper have important managerial and practical implications. First, they suggest that alignment, human capital utilization, and human capital transfer should function as key pillars to a firm's human-capital based strategy. Hiring the "best" workers thus entails not only considering the individual's level of productivity, but the degree to which the individual will contribute and benefit from the human capital strategy of the firm. Second, our results suggest that such considerations increase in importance with the size of the firm. Consequently, managers should more carefully manage and devote resources to managing the individual and firm-level human capital resources as size increases. Finally, successful entry strategies in knowledge-intensive industries must carefully consider the ultimate goal for the eventual human capital resource. Having such a goal in mind clarifies short-run human capital decisions at entry and helps founders avoid negative path dependent issues that will negatively influence firm success in the future.

In conclusion, while this paper has focused only on a single knowledge intensive industry, the theory and results suggest that a better understanding of human-capital based competitive advantages in knowledge-intensive industries is a worthwhile and fruitful avenue for future work. As the United States economy continues to transition towards firms whose primary productive resource is the human capital of its employed workers, understanding how individual and firm-level human capital resources can be created and leveraged lies at the heart of future strategy scholarship.

REFERENCES

Audretsch DB, Feldman MP. 1996. R&D spillovers and the geography of innovation and production. *The American economic review*. JSTOR **86**(3): 630–640.

Barney JB, Felin T. 2013. What Are Microfoundations? *Academy of Management Perspectives* **27**(2): 138–155.

Becker GS. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. London.

Byun, H., Frake, J., & Agarwal, R. (2018). Leveraging who you know by what you know: Specialization and returns to relational capital. *Strategic Management Journal*, *39*(7), 1803-1833.

Campbell BA, Coff R, Kryscynski D. 2012a. Rethinking Sustained Competitive Advantage from Human Capital. *Academy of Management Review* **37**(3): 376–395.

Campbell BA, Ganco M, Franco AM, Agarwal R. 2012b. Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal* **33**(1): 65–87.

Campbell-Hunt, C. (2000). What have we learned about generic competitive strategy? A meta-analysis. *Strategic Management Journal*, **21**(2): 127-154.

Chan TY, Li J, Pierce L. 2014. Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth. *Marketing Science* **33**(4): 463–484.

Chen, G., Huang, S., Meyer-Doyle, P., & Mindruta, D. (2020). Generalist vs. Specialist CEOs and Acquisitions: Two-sided Matching and the Impact of CEO Characteristics on Firm Outcomes. Strategic Management Journal: 1-32

Ching K, Forti E, Rawley E. 2019. Extemporaneous Coordination in Specialist Teams: The Familiarity Complementarity. Available at: https://papers.ssrn.com/abstract=3491456.

Campbell BA, Coff R, Kryscynski D. 2012. Rethinking sustained competitive advantage from human capital. *Academy of Management Review*. Academy of Management Briarcliff Manor, NY **37**(3): 376–395.

Cascio, W. F. (2019). Training trends: Macro, micro, and policy issues. *Human Resource Management Review, 29*(2), 284–297.

Coff RW. 1997. Human Assets and Management Dilemmas: Coping with Hazards on the Road to Resource-Based Theory. *The Academy of Management Review* **22**(2): 374–402.

Coff R, Kryscynski D. 2011. Invited editorial: Drilling for micro-foundations of human capital–based competitive advantages. *Journal of management*. Sage Publications Sage CA: Los Angeles, CA **37**(5): 1429–1443.

Collins, C., & Kehoe, R. (2017). Examining strategic fit and misfit in the management of knowledge workers. *ILR Review*, *70*(2), 308-335.

Conner KR, Prahalad CK. 1996. A Resource-Based Theory of the Firm: Knowledge versus Opportunism. *Organization Science* **7**(5): 477–501.

Crocker A, Eckardt R. 2014. A Multilevel Investigation of Individual- and Unit-Level Human Capital Complementarities. *Journal of Management* **40**(2): 509–530.

Ellison G, Glaeser EL. 1999. The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? *The American Economic Review* **89**(2): 311–316.

Felin T, Foss NJ. 2005. Strategic organization: a field in search of micro-foundations. *Strategic Organization* **3**(4): 441–455.

Fulmer IS, Ployhart RE. 2014. "Our Most Important Asset" A Multidisciplinary/Multilevel Review of Human Capital Valuation for Research and Practice. *Journal of Management* **40**(1): 161–192.

Galbraith, C., & Schendel, D. (1983). An empirical analysis of strategy types. *Strategic Management Journal* **4**(2): 153-173.

Garicano L. 2000. Hierarchies and the Organization of Knowledge in Production. *Journal of Political Economy* **108**(5): 874–904.

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach. *Journal of Labor Economics*, *28*(1), 1-49.

Gubler T. 2019. Connected, but Qualified? Social Affiliations, Human Capital, and Service Professional Performance. *Organization Science* **30**(5): 912–936.

Gubler T, Cooper R. 2019. Socially advantaged? How social affiliations influence access to valuable service professional transactions. *Strategic Management Journal* **0**(0). Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.3082.

Jolliffe, I.T. and Cadima, J. 2016 Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A* **374**: 20150202

Kogut B, Zander U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science* **3**(3): 383–397.

Kogut B, Zander U. 1996. What Firms Do? Coordination, Identity, and Learning. *Organization Science* **7**(5): 502–518.

Lazear EP. 2009. Firm-Specific Human Capital: A Skill-Weights Approach. *Journal of Political Economy* **117**(5): 914–940.

Lepak DP, Snell SA. 1999. The Human Resource Architecture: Toward a Theory of Human Capital Allocation and Development. *The Academy of Management Review* **24**(1): 31–48.
Levitt SD, Syverson C. 2008. Market Distortions When Agents Are Better Informed: The Value of Information in Real Estate Transactions. *Review of Economics and Statistics* **90**(4): 599–611.
Nagle, F., & Teodoridis, F. (2020). Jack of all trades and master of knowledge: The role of diversification in new distant knowledge integration. *Strategic Management Journal*, *41*(1), 55-85
Nyberg AJ, Moliterno TP, Hale D, Lepak DP. 2014. Resource-Based Perspectives on Unit-Level Human Capital A Review and Integration. *Journal of Management* **40**(1): 316–346.
Nyberg A, Reilly G, Essman S, Rodrigues J. 2018. Human capital resources: a call to retire settled debates and to start a few new debates. *The International Journal of Human Resource Management*. Routledge **29**(1): 68–86.
Ployhart RE, Moliterno TP. 2011. Emergence of the Human Capital Resource: A Multilevel Model. *Academy of Management Review* **36**(1): 127–150.
Ployhart RE, Cragun OR. 2017. Human capital resource complementarities. *The Oxford handbook of talent management*. Oxford University Press : 134–149.
Ployhart RE, Nyberg AJ, Reilly G, Maltarich MA. 2014. Human Capital Is Dead; Long Live Human Capital Resources! *Journal of Management* **40**(2): 371–398.
Raffiee J, Byun H. 2019. Revisiting the Portability of Performance Paradox: Employee Mobility and the Utilization of Human and Social Capital Resources. *Academy of Management Journal*. Academy of Management **63**(1): 34–63.
Rosen S. 1983. Specialization and Human Capital. *Journal of Labor Economics* **1**(1): 43–49.
Rosenthal SS, Strange WC. 2004. Evidence on the nature and sources of agglomeration economies. In *Handbook of regional and urban economics*. Elsevier, 4: 2119–2171.
Smith A. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations: 1776*. Adam Smith Institute.
Weller I, Hymer CB, Nyberg AJ, Ebert J. 2019. How matching creates value: Cogs and wheels for human capital resources research. *Academy of Management Annals*. Briarcliff Manor, NY **13**(1): 188–214.
Zenger TR, Felin T, Bigelow L. 2011. Theories of the Firm–Market Boundary. *The Academy of Management Annals* **5**(1): 89–133.
Zwick T, Frosch K, Hoisl K, Harhoff D. 2017. The power of individual-level drivers of inventive performance. *Research Policy* **46**(1): 121–137.

FIGURES AND TABLES

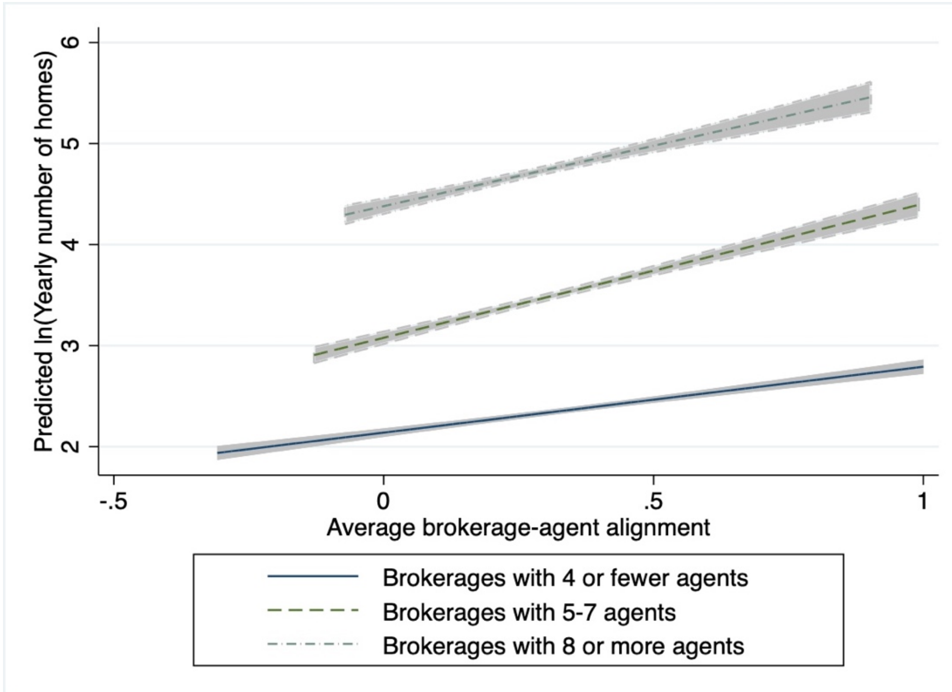

Figure 1: Brokerage-agent alignment is strongly positively associated with performance, and this relationship is stronger for brokerages with size above the median (4)

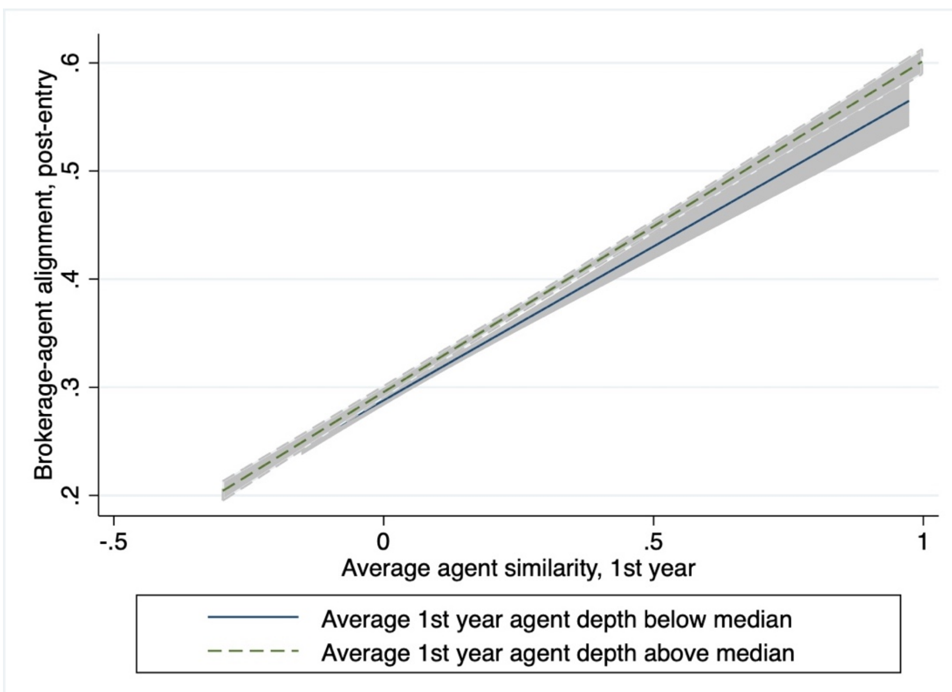

Figure 2: Agent similarity in entrant brokerages is strongly positively associated with brokerage-agent alignment in future years

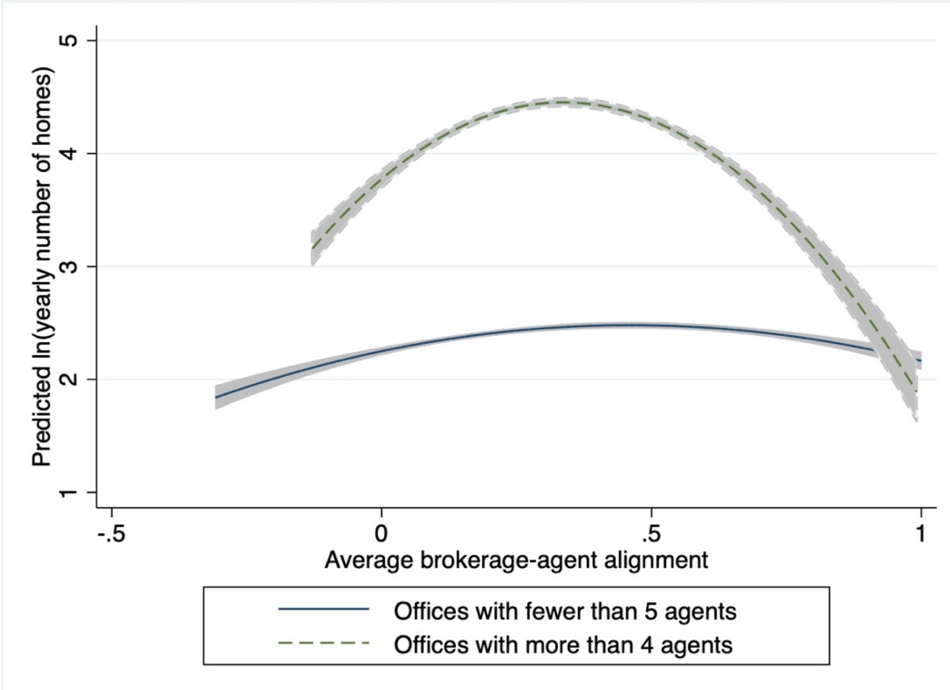

Figure 3: Within-brokerage, performance has an inverse-U-shaped relationship with brokerage-agent alignment, and this relationship intensifies as brokerage size increases

Table 1: Descriptive Statistics for Brokerage Performance Models

Variable	Obs	Mean	Std. Dev	Min	Max	Correlations (1)	(2)	(3)	(4)	(5)	(6)
Brokerage yearly number of homes	5932	63.401	140.146	1	1970	1.000					
Brokerage-agent alignment	5932	.315	.25	-.308	1	0.005	1.000				
Average brokerage scope before current year	5932	10.393	9.107	1	49.5	0.575	0.037	1.000			
Average brokerage size before current year	5932	6.947	13.191	1	178.875	0.747	-0.014	0.702	1.000		
Average number of listings in brokerage zip codes before current year	5932	898.665	259.081	35	3062	-0.087	-0.115	-0.085	-0.061	1.000	
Depth of human capital profile	5932	.59	.534	.162	5.028	-0.060	0.394	-0.252	-0.106	0.032	1.000
Current brokerage size	5932	9.638	19.646	2	332	0.892	-0.068	0.554	0.812	-0.048	-0.106
Current brokerage scope	5932	13.297	11.676	1	54	0.723	-0.044	0.780	0.616	-0.082	-0.226
Current average number of listings in brokerage zip codes	5932	859.45	302.564	120	3062	-0.109	-0.120	-0.180	-0.132	0.376	0.079
Current average agent experience	5932	62.146	85.98	1	1290.5	0.111	0.320	0.278	0.066	-0.060	0.018
Office age in years	5932	4.743	3.369	1	16	0.028	0.170	0.173	0.124	-0.067	-0.014
Broker franchise (dummy)	5932	.185	.389	0	1	0.310	-0.116	0.226	0.329	-0.067	-0.137

Variable	Obs	Mean	Std. Dev	Min	Max	Correlations (7)	(8)	(9)	(10)	(11)	(12)
Current brokerage size	5932	9.638	19.646	2	332	1.000					
Current brokerage scope	5932	13.297	11.676	1	54	0.694	1.000				
Current average number of listings in brokerage zip codes	5932	859.45	302.564	120	3062	-0.090	-0.169	1.000			
Current average agent experience	5932	62.146	85.98	1	1290.5	-0.004	0.195	-0.203	1.000		
Office age in years	5932	4.743	3.369	1	16	0.025	0.006	-0.185	0.182	1.000	
Broker franchise (dummy)	5932	.185	.389	0	1	0.346	0.297	-0.067	0.003	-0.001	1.000

Table 2: Descriptive Statistics for Building Human Capital Alignment Models

Variable	Obs	Mean	Std. Dev.	Min	Max	Correlations (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average yearly brokerage-agent alignment, post-entry	3475	0.339	0.242	-0.308	1	1.000							
Depth of brokerage-level human capital profile, post-entry	3475	0.621	0.582	0.162	5.028	0.406	1.000						
Average agent similarity, 1st year	3475	0.158	0.257	-0.298	.998	0.326	0.129	1.000					
Average agent human capital depth, 1st year	3475	0.410	0.336	0	2.416	0.184	0.284	0.374	1.000				
Brokerage size (# of agents), post-entry	3475	10.797	21.204	2	332	-0.117	-0.113	-0.052	0.013	1.000			
Brokerage average agent experience in number of homes, post-entry	3475	70.622	95.585	1	1290.5	0.299	-0.005	0.335	0.156	-0.037	1.000		
Office age in years, post-entry	3475	4.424	3.266	1	16	0.182	0.015	-0.062	-0.054	-0.016	0.232	1.000	
Broker franchise (dummy)	3475	0.194	0.395	0	1	-0.130	-0.163	-0.045	-0.050	0.386	-0.005	-0.008	1.000

Table 3: Main Effect of Brokerage-Agent Human Capital Alignment on Brokerage Performance

	(1)	(2)	(3)	(4)
DV:	log(Brokerage yearly number of homes)	log(Brokerage yearly number of homes)	log(Brokerage yearly number of homes)	log(Brokerage yearly number of homes)
Brokerage-agent alignment	.483	.099	.208	-.243
	(.125)	(.049)	(.125)	(.067)
Log(Current brokerage size)		.527	.99	.441
		(.019)	(.026)	(.026)
Alignment x log(size)			.554	.323
			(.08)	(.053)
log(Average brokerage scope before current year)		.05		.061
		(.02)		(.02)
log(Average brokerage size before current year)		-.029		-.039
		(.021)		(.021)
log(Average number of listings in brokerage zip codes before current year)		-.09		-.067
		(.031)		(.031)
Depth of human capital profile		.393		.379
		(.029)		(.031)
log(Current brokerage scope)		.847		.846
		(.018)		(.018)
log(Current average number of listings in brokerage zip codes)		.008		.129
		(.037)		(.013)
log(Current average agent experience)		.14		.006
		(.012)		(.037)
Office age in years		-.008		-.009
		(.003)		(.003)
Broker franchise (dummy)		-.04		-.04
		(.03)		(.028)
Constant	2.876	.412	1.381	.402
	(.102)	(.304)	(.08)	(.31)
Observations	5932	5932	5932	5932
R-squared	.013	.903	.69	.905
Year FE	Yes	Yes	Yes	Yes
Brokerage FE	No	No	No	No

Standard errors clustered at brokerage level (1,423 clusters) in parentheses

Table 4: Brokerage-Agent Alignment is Less Beneficial for Brokerages with Specialized Firm-Level Human Capital Strategies

	(1) log(Brokerage yearly number of homes)	(2) log(Brokerage yearly number of homes)	(3) log(Brokerage yearly number of homes)	(4) log(Brokerage yearly number of homes)
Size/breadth-focused HC profile (dummy)	-.051			-.029
	(.074)			(.076)
Demand-focused HC profile (dummy)		.038		.068
		(.042)		(.041)
Depth-focused HC profile (dummy)			.428	.439
			(.079)	(.079)
Brokerage-agent alignment	.094	.11	.176	.182
	(.049)	(.049)	(.038)	(.04)
Size-focused x alignment	.58			.59
	(.212)			(.219)
Demand-focused x alignment		-.16		-.138
		(.091)		(.091)
Depth-focused x alignment			-.371	-.384
			(.123)	(.125)
log(Average brokerage scope before current year)	.058	.05	.058	.068
	(.02)	(.02)	(.018)	(.019)
log(Average brokerage size before current year)	-.041	-.03	-.039	-.053
	(.023)	(.021)	(.021)	(.021)
log(Average number of listings in brokerage zip codes before current year)	-.089	-.089	-.075	-.078
	(.031)	(.032)	(.031)	(.032)
Depth of human capital profile	.401	.391	.285	.293
	(.029)	(.029)	(.035)	(.035)
log(Current brokerage size)	.85	.846	.856	.859
	(.018)	(.018)	(.018)	(.018)
log(Current brokerage scope)	.517	.528	.525	.512
	(.02)	(.019)	(.019)	(.02)
log(Current average number of listings in brokerage zip codes)	.135	.14	.126	.121
	(.013)	(.012)	(.011)	(.011)
log(Current average agent experience)	.008	.012	-.002	-.003
	(.037)	(.038)	(.035)	(.036)
Office age in years	-.008	-.007	-.008	-.008
	(.003)	(.003)	(.003)	(.003)
Broker franchise (dummy)	-.043	-.041	-.017	-.019
	(.029)	(.03)	(.029)	(.029)
Constant	.416	.382	.399	.43
	(.303)	(.319)	(.306)	(.317)
Observations	5932	5932	5932	5932
R-squared	.903	.903	.906	.907
Year FE	Yes	Yes	Yes	Yes
Brokerage FE	No	No	No	No

Standard errors, clustered at the brokerage level (1,423 clusters) are in parentheses

Table 5: Post-Entry Brokerage-Agent Alignment is Positively Associated with Entry-Year Agent Similarity

DV:	(1) Average yearly brokerage-agent alignment	(2) Average yearly brokerage-agent alignment	(3) Average yearly brokerage-agent alignment	(4) Average yearly brokerage-agent alignment
Average agent similarity, 1st year	0.307	0.282	0.210	0.199
	(0.030)	(0.030)	(0.031)	(0.031)
Average agent human capital depth, 1st year		0.052		0.029
		(0.027)		(0.025)
Similarity x depth				
log(office size)			-0.04	-0.041
			(0.007)	(0.007)
log(average agent experience)			0.066	0.064
			(0.007)	(0.007)
Office age in years			0.012	0.012
			(0.002)	(0.002)
Broker franchise			-0.018	-0.016
			(0.015)	(0.015)
Constant	0.291	0.273	0.210	0.206
	(0.011)	(0.015)	(0.032)	(0.032)
Observations	3475	3475	3475	3475
R-squared	0.106	0.111	0.256	0.257
Year FE	No	No	Yes	Yes

Standard errors clustered at brokerage level (845 clusters) in parentheses

APPENDIX

Table A1: Results of Principal Component Analysis of Human Capital Profiles

Component	(1) Eigenvalue	(2) Difference	(3) Proportion	(4) Cumulative
Component 1	1.9015	0.9569	0.4754	0.4754
Component 2	0.9446	0.0171	0.2361	0.7115
Component 3	0.9275	0.7010	0.2319	0.9434
Component 4	0.2265		0.0566	1.0000

Principal components (eigenvectors)

Variable	Component 1	Component 2	Component 3	Component 4
Brokerage Scope Z-Score	0.6673	0.1688	0.1017	0.7183
Brokerage Size Z-Score	0.6426	0.3200	0.1087	-0.6876
Brokerage Demand Z-Score	-0.2719	0.3387	0.8996	0.0457
Brokerage Depth Z-Score	-0.2604	0.8685	-0.4106	0.0959

Note: Although it is common practice to only use components that combine to explain about 70% of the data (Jolliffe and Cadima, 2016), we chose to keep Component 3 as well as 2 because of the fact that it accounts for close to the same amount of the variation.

Table A2: Main Effect of Brokerage-Agent Human Capital Alignment on Brokerage Performance with Brokerage Fixed Effects

	(1) log(Brokerage yearly number of homes)	(2) log(Brokerage yearly number of homes)	(3) log(Brokerage yearly number of homes)	(4) log(Brokerage yearly number of homes)	(5) log(Brokerage yearly number of homes)	(6) log(Brokerage yearly number of homes)
Brokerage-agent alignment	-.507	.064	-.187	.025	.122	-.829
	(.102)	(.058)	(.108)	(.136)	(.092)	(.209)
Brokerage-agent alignment²			.309			1.266
			(.126)			(.255)
log(Current brokerage size)		.443	.450	1.042	.458	.38
		(.026)	(.026)	(.033)	(.031)	(.036)
Alignment x log(size)				.04	-.058	.64
				(.098)	(.066)	(.171)
Alignment² x log(size)						-.976
						(.224)
log(Average brokerage scope before current year)		.055	.055		.053	.058
		(.025)	(.025)		(.025)	(.026)
log(Average brokerage size before current year)		.053	.054		.057	.045
		(.03)	(.030)		(.03)	(.03)
log(Average number of listings in brokerage zip codes before current year)		.081	.070		.08	.077
		(.056)	(.056)		(.057)	(.057)
Depth of human capital profile		-.018	-.027		-.017	-.025
		(.063)	(.063)		(.063)	(.062)
log(Current brokerage scope)		.858	.857		.858	.859
		(.023)	(.023)		(.023)	(.023)
log(Current average number of listings in brokerage zip codes)		.002	.003		.006	.008
		(.04)	(.04)		(.016)	(.016)
log(Current average agent experience)		.006	.008		.003	.008
		(.016)	(.016)		(.04)	(.04)
Office age in years		-.031	-.031		-.031	-.03
		(.005)	(.005)		(.005)	(.005)
Constant	3.367	-.049	.025	1.729	-.072	.013
	(.098)	(.497)	(.501)	(.083)	(.5)	(.501)
Observations	5932	5932	5932	5932	5932	5932
R-squared	.833	.959	.959	.914	.959	.959
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at brokerage level (1,423 clusters) in parentheses

Table A3: Performance on Brokerage-Agent Alignment for Different Human Capital Strategies – Alternative Classifications

	(1) log(Brokerage yearly number of homes)	(2) log(Brokerage yearly number of homes)	(3) log(Brokerage yearly number of homes)	(4) log(Brokerage yearly number of homes)
Size/breadth-focused HC profile (dummy)	-.203			-.187
	(.042)			(.044)
Demand-focused HC profile (dummy)		-.081		-.112
		(.03)		(.029)
Depth-focused HC profile (dummy)			.228	.194
			(.029)	(.028)
Brokerage-agent alignment	.062	.15	.141	.112
	(.049)	(.059)	(.048)	(.062)
Size-focused x alignment	.446			.438
	(.105)			(.115)
Demand-focused x alignment		-.155		-.092
		(.061)		(.062)
Depth-focused x alignment			-.184	-.13
			(.066)	(.067)
log(Average brokerage scope before current year)	.052	.049	.063	.064
	(.02)	(.019)	(.019)	(.019)
log(Average brokerage size before current year)	-.023	-.036	-.027	-.03
	(.022)	(.021)	(.021)	(.021)
log(Average number of listings in brokerage zip codes before current year)	-.094	-.033	-.077	-.02
	(.031)	(.033)	(.031)	(.034)
Depth of human capital profile	.39	.36	.338	.308
	(.029)	(.029)	(.03)	(.031)
log(Current brokerage size)	.851	.846	.858	.858
	(.018)	(.018)	(.018)	(.018)
log(Current brokerage scope)	.539	.525	.521	.53
	(.019)	(.018)	(.019)	(.019)
log(Current average number of listings in brokerage zip codes)	.136	.137	.127	.122
	(.012)	(.012)	(.011)	(.011)
log(Current average agent experience)	.002	.064	.001	.058
	(.037)	(.04)	(.037)	(.04)
Office age in years	-.009	-.003	-.008	-.004
	(.003)	(.003)	(.003)	(.003)
Broker franchise (dummy)	-.048	-.034	-.032	-.031
	(.029)	(.029)	(.029)	(.028)
Constant	.481	-.245	.314	-.318
	(.303)	(.35)	(.311)	(.36)
Observations	5932	5932	5932	5932
R-squared	.904	.904	.906	.908
Year FE	Yes	Yes	Yes	Yes
Brokerage FE	No	No	No	No

Standard errors, clustered at the brokerage level (1,423 clusters) are in parentheses

Table A4 Brokerage-agent Alignment and Agent Mobility Results

	(1)	(2)	(3)
DV:	log(Brokerage yearly number of homes)	log(Brokerage yearly number of homes)	Agent departures
Brokerage-agent alignment	.535	.077	-.438
	(.111)	(.047)	(.176)
Previous departures	.020	.001	
	(.003)	(.001)	
Alignment x departures	.014	.009	
	(.010)	(.002)	
log(Average brokerage scope before current year)		.062	-.041
		(.019)	(.058)
log(Average brokerage size before current year)		-.052	.095
		(.02)	(.06)
log(Average number of listings in brokerage zip codes before current year)		-.083	.104
		(.03)	(.093)
Depth of human capital profile		.4	.391
		(.028)	(.073)
log(Current brokerage size)		.866	.429
		(.018)	(.059)
log(Current brokerage scope)		.13	-.014
		(.012)	(.031)
log(Current average number of listings in brokerage zip codes)		.018	.268
		(.036)	(.116)
log(Current average agent experience)		-.007	-.022
		(.003)	(.008)
Office age in years		-.037	-.016
		(.028)	(.057)
Broker franchise (dummy)	2.719	.359	-3.887
	(.048)	(.296)	(.911)
Constant	5932	5932	5932
(Pseudo) R^2	.259	.907	.16
Year FE	Yes	Yes	Yes
Brokerage FE	No	No	No

Standard errors, clustered at the brokerage level (1,423 clusters) are in parentheses